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(54) Title: COMPRESSION OF HYPERDATA WITH ORASIS MULTISEGMENT PATTERN SETS (CHOMPS) (57) Abstract The Intelligent Hypersensor Processing System (IHPS) is a system for the rapid detection of small, weak, or hidden objects, substances, or patterns embedded in complex backgrounds, providing fast adaptive processing for demixing and recognizing patterns or signatures in data provided by certain types of "hypersensors". This system represents an alternative to prior systems for hidden object detection by solving the problems encountered when attempting to detect hidden objects/targets in dynamic scenarios at real-time. The CHOMPS version of IHPS provides an efficient means of processing, compressing and manipulating the vast quantities of data collected by the sensors. CHOMPS uses the Adaptive Learning Module Pipeline to construct a compressed data set, along with the necessary scene mapping data, facilitating the efficient storage, download and the later reconstruction of the complete data set with minimal deterioration of signal information.		

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COMPRESSION OF HYPERDATA WITH ORASIS MULTISEGMENT PATTERN SETS (CHOMPS)

BACKGROUND OF THE INVENTION

1 The present invention relates generally to processing signals, and more particularly to a
2 system for the rapid compression of hypersensor data sets that contain objects, substances, or
3 patterns embedded in complex backgrounds. A hypersensor is a sensor which produces as its
4 output a high dimensional vector or matrix consisting of many separate elements, each of which
5 is a measurement of a different attribute of the system or scene under construction. A
6 hyperspectral imager is an example of a hypersensor. Hypersensors based on acoustic or other
7 types of signals, or combinations of different types of input signals are also possible.

8 Historically there have been three types of approaches to the problems relating to the
9 detection of small, weak or hidden objects, substances or patterns embedded in complex
10 backgrounds.

11 The first approach has been to use low dimensional sensor systems which attempt to detect
12 a clean signature of a well known target in some small, carefully chosen subset of all possible
13 attributes, e.g., one or a few spectral bands. These systems generally have difficulty when the
14 target signature is heavily mixed in with other signals, so they typically can detect subpixel
15 targets or minority chemical constituents of a mixture only under ideal conditions, if at all. The
16 target generally must fill at least one pixel, or be dominant in some other sense as in some
17 hyperspectral bands. Also, the optimal choice of bands may vary with the observing conditions
18 or background (e.g. weather and lighting), so such systems work best in stable, predictable
19 environments. These systems are simpler than the high dimensional sensors (hypersensors), but
20 they also tend to be less sensitive to subdominant targets and less adaptable.

21 The second approach has been to employ high dimensional sensor systems which seek to

1 detect well known (prespecified) targets in complex backgrounds by using Principle Components
2 Analysis (PCA) or similar linear methods to construct a representation of the background.
3 Orthogonal projection methods are then used to separate the target from the background. This
4 approach has several disadvantages. The methods used to characterize the background are
5 typically not 'real time algorithms'; they are relatively slow, and must operate on the entire data
6 set at once, and hence are better suited to post-processing than real time operation. The
7 background characterization can get confused if the target is present in a statistically significant
8 measure when the background is being studied, causing the process to fail. Also, the appearance
9 of the target signature may vary with the environmental conditions: this must be accounted for
10 in advance, and it is generally very difficult to do. Finally, these PCA methods are not well suited
11 for detecting and describing unanticipated targets, (objects or substances which have not been
12 prespecified in detail, but which may be important) because the representation of the background
13 constructed by these methods mix the properties of the actual scene constituents in an unphysical
14 and unpredictable way. PCA methods are also used for compression schemes however they have
15 many of the same shortcomings. Linear Vector Quantization (LVQ) is also used for compression.
16 Current LVQ schemes use minimum noise fraction (MNF) or average patterns of PCs to compress
17 the data, which are slow and require a priori knowledge of sensor characteristics.

18 The more recent approach, is based on conventional convex set methods, which attempt
19 to address the 'endmember' problem. The endmembers are a set of basis signatures from which
20 every observed spectra in the dataset can be composed in the form of a convex combination, i.e.,
21 a weighted sum with non-negative coefficients. The non-negativity condition insures that the sum
22 can sensibly be interpreted as a mixture of spectra, which cannot contain negative fractions of any
23 ingredient. Thus every data vector is, to within some error tolerance, a mixture of endmembers.
24 If the endmembers are properly constructed, they represent approximations to the signature
25 patterns of the actual constituents of the scene being observed. Orthogonal projection techniques
26 are used to demix each data vector into its constituent endmembers. These techniques are

1 conceptually the most powerful of the previous approaches, but current methods for implementing
2 the convex set ideas are slow, (not real time methods) and cannot handle high dimensional pattern
3 spaces. This last problem is a serious limitation, and renders these methods unsuitable for
4 detecting weak targets, since every constituent of a scene which is more dominant than the target
5 must be accounted for in the endmember set, making weak target problems high dimensional. In
6 addition, current convex set methods give priority to the constituents of the scene which are
7 dominant in terms of frequency of occurrence, with a tendency to ignore signature patterns which
8 are clearly above the noise but infrequent in the data set. This makes them unsuitable for
9 detecting strong but small targets unless the target patterns are fully prespecified in advance.

10 When operating in high dimensional pattern spaces massive quantities of data must be
11 managed which requires hundreds of millions of computations for each pixel. Thus the need to
12 compress massive quantities of data for storage, download, and/or real time analysis becomes
13 increasingly important and equally elusive.

15 SUMMARY OF THE INVENTION

16 Accordingly, it is an object of this invention to compress multispectral data, while
17 preserving the spectral information for the detection of objects or substances embedded in
18 complex backgrounds.

19 Another object of this invention is accurate and quickly compress multidimensional
20 data sets from chemical, acoustic or other types of hypersensors capable of handling
21 multidimensional analysis.

22 Another object of this invention is to process signal and compress data with a fast set of
23 algorithms which provide a greatly reduced computational burden in comparison to existing
24 methods.

25 Another object of this invention is to compress hyperspectral or multispectral data in a
26 system employing parallel processing which offers true real time operation in a dynamic
27

1 scenario.

2 These and additional objects of this invention are accomplished by the structures and
3 processes hereinafter described.

4 The Compression of Hyperdata with ORASIS Multisegment Pattern Sets, (CHOMPS),
5 system is an improved version of the Intelligent Hypersensor Processing System (IHPS)
6 employing the CHOMPS algorithm to compress the size of the data output and increase the
7 computational efficiency of the IHPS prescreener operation or comparable operations in other
8 multidimensional signal processing systems. The CHOMPS configured prescreener employs a
9 structured search method used to construct the exemplar set with the minimum number of
10 operations. IHPS forms a series of pattern vectors through the concatenation of the outputs of
11 multiple sensors. The data stream from the sensors is entered into a processing system which
12 employs a parallel-pipeline architecture. The data stream is simultaneously sent to two
13 separate processor pipelines. The first processor pipeline, referred to as the demixer pipeline,
14 comprises the demixer module, which decomposes each pattern vector into a convex
15 combination of a set of fundamental patterns which are the constituents of the mixture. The
16 decomposition is accomplished using projection operations called 'Filter Vectors' generated in
17 the second pipeline, referred to as the adaptive learning pipeline, which contains the adaptive
18 learning module. The signature pattern of a weak constituent or an unresolved small target is
19 separated from background patterns which may hide the target pattern in the unmixed data.
20 Information detailing the composition of the demixed data patterns is sent to the
21 Display/Output Module along with information about the fundamental patterns and Filter
22 Vectors.

23 The CHOMPS embodiment of IHPS provides an efficient means of compressing and
24 manipulating the vast quantities of data collected by the sensors. CHOMPS uses the
25 Prescreener, the Demixer Pipeline and the Adaptive Learning Module Pipeline to construct a
26 compressed data set, along with the necessary scene mapping data, facilitating the efficient

1 storage, download and the later reconstruction of the complete data set with minimal
2 deterioration of signal information.

3 4 5 BRIEF DESCRIPTION OF THE DRAWINGS

6
7 Figure 1. is a representation of the data cube and the orientation of the spatial and wavelength
8 information in X , λ and T coordinates.

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10
11 Figure 2. is a block diagram of an embodiment of IHPS showing the system's parallel structure.

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9 Figure 19. is a logic flowchart of the CHOMPS wavespace compression mode.

10
11 Figure 20. is a logic flowchart of the CHOMPS endmember compression mode.

12
13
14
15 DETAILED DESCRIPTION OF THE PREFERRED EMBODIMENT

16
17 Referring now to the Figures, wherein like reference characters indicate like elements
18 throughout the several views, Figure 1 is a representation of the data cube and the orientation
19 of the spatial and wavelength information. IHPS forms a series of pattern vectors through
20 the concatenation of the outputs of multiple sensors. Each sensor measures a different
21 attribute of the system being observed, and has a consistent relationship to all the other
22 sensors.

23 In a preferred embodiment the optical system may be employed on an aircraft or
24 spacecraft. As the craft flies over or in close proximity to an area of interest, Hypersensor 10
25 scans the scene or area of interest by taking successive snapshots of the scene below. Each
26 snapshot constitutes a frame of spectral data. The spectral data is scanned frame by frame 210
27 and displayed as variations in intensity. In the optical example, a frame 210 is the diffracted
28 image on a two dimensional focal plane of a narrow slit which accepts light from a narrow
29 linear strip of the scene. Variations of the optical sensor layout are possible. Each frame
30 210 comprises multiple lines 205; each line 205 being the spectral characteristic for a specific
31 point in the scene which correlates to a specific coordinate of the area scanned. Each frame
32 210 is configured such that the spatial information is expressed along the X axis and
33 wavelength information is contained in the λ direction. Data cube 200, as illustrated in Figure
34 1, is created by the concatenation of successive frames 210 (different spatial strips) and

1 represents the observed spectral data of the scene provided by the hypersensor. The observed
2 spectral data, which is used to create data cube 200 is expressed in vector form, and processed
3 one spatial pixel, i.e. one spectrum, at a time. Each pixel is fed into a preprocessor (not
4 shown) which performs normalization and purges bad spectral data, bad spectral data being
5 data corrupted or otherwise useless due to incomplete spectral information.

6 Referring now to figure 2, which shows a block diagram of the basic system
7 architecture, the data stream from the sensors is entered into a processing system 100 which
8 employs a parallel-pipeline architecture. The data stream is simultaneously sent to two
9 separate processor pipes one for demixing 140, and one for adaptive learning operations 150.
10 Demixer Module 20, decomposes each pattern vector into a convex combination of a set of
11 fundamental patterns which are the constituents of the mixture. The decomposition is
12 accomplished using projection operations called 'Filter Vectors' generated in the second
13 pipeline by the Adaptive Learning Module 30. Hypersensor 10 collects data and transmits the
14 collected data to prescreener 50. Prescreener 50 constructs a survivor set by extracting
15 exemplars, or data collected by hypersensor 10 which may contain new or useful information.
16 The signature pattern of a weak constituent or an unresolved small target is separated from
17 background patterns which may hide the target pattern in the unmixed data. A priori
18 knowledge about the signatures of known targets can be used, and approximate signatures of
19 unknown constituents are determined automatically. Information detailing the composition of
20 the demixed data patterns is sent to Output Module 40, along with information about the
21 fundamental patterns and Filter Vectors. Learning module 30, performs minimization
22 operations and projects the exemplar set information into a reduced dimensional space,
23 generating endmembers and filter vectors.

24 For other types of hypersensors, the spectral vectors produced by the sensor array
25 would be replaced by a vector of other types of data elements, such as the amplitudes of
26 different frequencies of sound. The organization of input data vectors may also vary somewhat

1 depending on the type of sensor. Aside from these sensor-dependent variations in the type and
 2 organization of the input data, the operation, capabilities, and output of the processing system
 3 would remain the same.

4 Again referring to figure 2, the vector data d is then simultaneously fed into the
 5 adaptive learning and demixer processor pipes. This parallel processing architecture
 6 illustrated in the figure is a preferred structure, however, this system, algorithms and
 7 hardware contained herein may be employed in a system with a traditional architecture. The
 8 demixer processor pipeline 140 comprises demixer module 20 which decomposes each data
 9 vector d_k into a convex combination of a set of fundamental patterns, which are endmembers or
 10 constituents of the mixture. The decomposition is accomplished using projection operators
 11 called 'Filter Vectors' generated by the adaptive learning module 30.

12 The filter vectors F_i are a set of optimal matched filters: they are the smallest vectors
 13 which will satisfy the condition:

$$F_i \cdot E_j = \delta_{ij}$$

14 where δ_{ij} is the Kronecker delta function (δ_{ij} equals 1 if $i = j$ and 0 otherwise) and the vectors
 15 E_j are the endmembers of the scene, thus, each data vector d_k (spectrum) is a convex
 16 combination of endmembers plus a noise vector N_k .

$$d_k = \sum_{j=1}^n c_{kj} E_j + N_k \quad c_{kj} \geq 0$$

18
 19 The dot product of d_k with filter vector F_j , where j is the j th endmember, yields the coefficient
 20 of endmember E_j in the sum, plus a small error due to noise.

$$F_j \cdot d_k = \sum_{j=1}^n c_{kj} F_j \cdot E_j + F_j \cdot N_k \approx c_{kj}$$

1 This determines the contribution which endmember J makes to the spectrum d_k . The filter
 2 vectors are optimal matched filters which are found by solving the minimization problem
 3 (smallest magnitude) described above, subject to the constraint imposed by the orthogonality
 4 condition. The solution has the form

$$\underline{\underline{F}} = \underline{\underline{M}}^{-1} \underline{\underline{E}}$$

5
 6 where the filter vectors are the rows of the matrix $\underline{\underline{F}}$, the endmembers (assumed to have unit
 7 magnitude) are the rows of the matrix $\underline{\underline{E}}$, and the matrix $\underline{\underline{M}}$ has the elements $M_{ij} = E_i \cdot E_j$.

8 Filter vectors allow the signature pattern of a weak constituent or unresolved small
 9 target to be separated from background patterns which may hide the target pattern in the
 10 spectral data. Filter vectors demix the spectrum by projecting out one endmember at a time.

11 CHOMPS is not limited to filter vector manipulations. There are several methods
 12 known in the art to demix the spectrum, such as the use of spectral matched filters (SMF) or
 13 pseudoiverses, any of which may be suitable for compression use.

14 Information c_{kj} detailing the composition of the demixed data spectrum is sent to
 15 Display/Output module 40 from the demixer module through the demixer pipeline 140, along
 16 with information E_j about the fundamental spectra patterns, and filter vectors from adaptive
 17 learning module 30 via the adaptive learning pipeline 150. Display/Output module 40,
 18 displays the distribution of the constituents of the scene, transmits, or stores the demixed data
 19 for later analysis.

20 The adaptive learning or second processor pipeline 150 comprises prescreener 50, and
 21 adaptive learning module 30. The object of prescreener 50, is to generate the exemplar
 22 ensemble $\{S\}$ to a user specified precision by comparing each incoming spectral vector d to the
 23 up-to-date exemplar set $\{S\}$.

24 Referring now to figure 3, prescreener 50 receives data vectors d from preprocessor
 25 (not shown) and generates a reduced set of vectors or exemplar ensemble called the survivor
 26 or exemplar set 55. Exemplar set 55 is then transmitted to adaptive learning module 30.

1 Prescreener 50 reduces the amount of data processed by discarding spectral signatures which
2 contain redundant information. This reduces the computational burden on the other elements
3 of the learning pipeline. The exemplar set 55 is generally less than 1% of the total input
4 stream, but its size varies depending upon the conditions and applications.

5 In CHOMPS, prescreener 50 is implemented in several different ways, depending on
6 the application's timeliness requirements and the processing system hardware. In a preferred
7 embodiment the prescreener module is implemented using multithreaded or messaging
8 multiprocessor operation. Referring now to figure 14 which shows a block diagram of ALM
9 processor pipeline 150 employing multithreaded operation, data generated by sensor 10 passes
10 through multiple processor pipes. The data set is segmented so that each prescreener 50
11 processes a different section of the input stream. The prescreeners are coupled to allow each
12 prescreener module 50 to share exemplar set information, updating and receiving updates from
13 the other prescreeners. This allows each prescreener to build a complete exemplar set $\{S\}$
14 which reflects the exemplars extracted from vector data set $\{d\}$ by each prescreener 50. In
15 multithreaded operation the prescreeners 50 can also be decoupled, for independent operation.
16 In this mode, each prescreener processes the complete data set, and a separate software
17 module reconciles the output of the parallel prescreeners into a single exemplar set.

18 The complete and updated exemplar set $\{S\}$ is then passed to the ALM 30 for
19 endmember generation. The endmember data and filter vectors are passed to the output
20 module.

21 CHOMPS is thus able to quickly and efficiently sample a very large data set and
22 generate a exemplar set by prescreening large "chunks" of the data set simultaneously.
23 Coupled with the compression and computational management techniques discussed
24 throughout this text, the ability to employ parallel processing at the prescreener level results
25 in a substantial improvement in the efficiency of IHPS and CHOMPS significantly extending
26 the real time operation envelope.

1 The multiprocessor configuration illustrated in figure 14 may also be employed using
2 multiple prescreeners distributed in a network of machines. CHOMPS is also capable of being
3 employed using a single threaded operation, where each vector is processed sequentially by a
4 single processor.

5 Figure 3 illustrates the flowchart of the logical operation of prescreener 50.
6 Prescreener 50 generates the exemplar set {S} by comparing 54 the data spectra of the most
7 recent pixel sampled with existing members of the exemplar set 55. The exemplar set is
8 generated by performing dot operations in accordance to the relation:

$$d_i \cdot S_j > 1 - \epsilon$$

9
10
11
12 where, d_i is the i th newly sampled data vector, S_j is an existing exemplar set vector, and ϵ is
13 variable controlling threshold sensitivity. Here, the vectors d_i and S_j are assumed to be
14 normalized to unit magnitude. Thus, the condition $d_i \cdot S_j = 1$ means that the two vectors are
15 identical and the condition $d_i \cdot S_j > 1 - \epsilon$ means that they are almost identical if ϵ is small.
16 Vectors for d_i which meet the above condition for any exemplar S_j are discarded 52 and the
17 next vector is examined. Discarded vectors are not included in the exemplar set. The
18 rejection count for each exemplar is stored in an array for future recall. The value of ϵ , which
19 is set by the operator or a control system, is a function of the exemplar set size desired,
20 memory length for exemplar set values, desired thruput of data and the noise in the signal 56.
21 Generally, as the value of ϵ is increased, the sensitivity of the system is decreased. The pruner
22 51 is a memory management device which determines when a exemplar set vector S_j should be
23 purged from the memory. Pruner 51 monitors the exemplar set 55, and adjusts the control
24 parameters to control exemplar set size. This is accomplished by setting the value for ϵ 54,
25 and the maximum allowed age of a exemplar, which determines the threshold for additions to

1 the exemplar set and the time a exemplar is allowed to remain in the exemplar set without
2 being regenerated.

3 The exemplar set vector, S_j , used in the $d_i \cdot S_j > 1-\epsilon$ comparison is preferably chosen
4 via the use of a structured search technique to minimize the number of dot operations while
5 offering thorough analysis of the exemplar set 55. This may be accomplished by comparing 54
6 the newly sampled data vector with the most recent vectors entered into the exemplar set.
7 Other search methods which minimize the number of operations necessary for thorough
8 matching are also suitable. CHOMPS employs several such structured techniques designed to
9 minimize the number of operations necessary for effective prescreener operation discussed in
10 detail below.

11 The computational management techniques employed by CHOMPS is referred to as
12 Focus searching. Focus searching includes priority searching and zone searching which
13 generally relate to focusing the comparisons of the incoming data vector d_i to the exemplars S_j
14 so that relevant exemplars can be quickly located, and to reduce the number of exemplar
15 comparisons necessary, before a determination can be made as to whether a new data vector d_i
16 is similar to an existing exemplar S_j .

17 In a priority search CHOMPS will assign a higher priority to some exemplars than
18 others on the basis of an exemplars age, past comparisons or some other statistical basis. The
19 exemplars designated with the higher priority are initially used in the $d \cdot S > 1-\epsilon$ prescreener
20 comparison. Exemplars with a lower priority are used later if necessary.

21 In a preferred embodiment, one such computational management technique CHOMPS
22 employs is in the form of a priority search technique called a Pop-up test. The pop up test uses
23 a data structure called a pop up stack. The pop-up stack is a subset of the exemplar set $\{S\}$
24 containing only the exemplar vectors S_j that most recently rejected an incoming spectral data
25 vector d_i . These vectors include the most recent exemplar entry, and the exemplar that most
26 recently rejected a candidate exemplar. When a data vector is determined to be dissimilar

1 from the other exemplar set members it is entered into the pop up stack.

2 Referring now to figure 16, which shows a flowchart of the pop up stack test,
3 prescreener first receives a data vector d_N from the sensor 556, where N is just the order in
4 which the vector is received. Prescreener then performs the standard dot product comparison
5 to determine if d_N is similar to S_j . If the condition in the inequality is met, d_N is rejected as
6 similar to S_j or repetitive data 565 and the next data vector d_{N+1} is retrieved, 566. S_j is then
7 placed at the top of the stack 567, resulting in the next data vector sampled being compared to
8 S_j first. If the condition is not met, the prescreener retrieves the next exemplar in the stack S_{j+1} ,
9 555, and repeats the $d_N \bullet S_j > 1-\epsilon$ comparison 564 where $S_j = S_{j+1}$. If the condition is met,
10 prescreener again rejects d_N as similar 565, places S_{j+1} at the top of the stack 567 and retrieves
11 the next data vector d_{N+1} for comparison 566, 556. If the condition is not met, the prescreener
12 will go on to the next text 570.

13 The pop up stack thus gives priority to the last exemplar to reject a data vector as
14 similar. Called a rejector, this exemplar is statistically more likely to be similar to the next
15 incoming data vector than an exemplar with a more distant rejection history. Thus the pop up
16 test improves the chances of quickly classifying a vector as similar with a single comparison
17 operation. Other variations of the pop up stack are possible, for instance the newest rejector
18 may not be assigned highest priority (used in first comparison), it may just be given a higher
19 priority the majority of the other exemplars.

20 Preferably, the pop up test is performed for no more than 2 or 3 cycles, however,
21 multiple iterations of the pop up test may be performed. In the preferred embodiment, after 2
22 or 3 cycles, CHOMPS next performs a Zone search.

23 In a zone search CHOMPS chooses a point of reference, and defines the exemplar set
24 $\{S\}$ and the incoming data vectors d according to their relation to the reference. The
25 exemplar data set $\{S\}$ is labeled and stored according to some defined relationship with the
26 reference point structured to allow the prescreener to quickly recall exemplars S_j which meet

1 parameter in relation to data vector d_i . Thus CHOMPS can use the incoming data vectors
2 relation to the reference point to define a zone of exemplars to compare with d_i and determine
3 whether the incoming data vector d_i contains new information.

4 In a preferred embodiment CHOMPS designates a vector as a reference point. These
5 vectors are referred to as reference vectors. The reference vector is used as a reference point
6 from which the vectors of the exemplar set $\{S\}$ and data set $\{d\}$ are defined. Reference
7 vectors may be arbitrary, however a further reduction in the number of computations
8 necessary is achieved if the reference vectors are selected such that the exemplar projections
9 yield the maximum possible spread in each reference direction. Reference vectors may be
10 chosen as approximations to the largest principal components of the current exemplar set. In a
11 preferred embodiment the reference vector is initially chosen arbitrarily, and once the
12 prescreener constructs the exemplar set, CHOMPS uses a Principal Components Analysis to
13 designate one or more reference vectors.

14 In the Principal Components Analysis, CHOMPS uses the exemplar vectors as well as
15 the rejection count for each exemplar to estimate the covariance matrix. As more image
16 pixels arrive, the reference vectors are updated, based on mission requirements and
17 considerations as to whether an update is beneficial. In CHOMPS, the data vectors are
18 addressed on the basis of their projection onto the reference vector.

19 Referring now to figure 15 which illustrates a reference vector R and exemplar set
20 vectors S_N projected onto it, the angle θ_N between the reference vector and each incoming
21 spectral vector is computed. The reference angle for each exemplar is stored in an array or
22 table along with a notation designating which vector the angle θ_N represents for future recall.

23 In a preferred embodiment the exemplar set data, the exemplar number and its
24 orientation to the reference vector is contained in a linked list or hash table, known in the art,
25 such that each exemplar can be quickly located and recalled by the prescreener as a function of
26 the reference angle θ_N . Thus, the actual reference angle need not be stored, the reference angle

1 is determined as a function of which address the entry occupies. As new entries to the linked
2 list are made the address pointers are changed, rather than shuffling and reloading the entire
3 array each time an exemplar is changed.

4 A preferred embodiment of CHOMPS also uses a form of the Bullseye test to locate the
5 exemplars in the current exemplar set which are likely to reject the new data vector d as
6 similar.

7 In the Bullseye test, CHOMPS uses the data vectors projection on the reference vector
8 in concert with the exemplars projection on the reference vector to eliminate all existing
9 exemplars that could not possibly match the incoming vector. CHOMPS accomplishes this by
10 constructing a cone which defines the zone in which possible matches may occur and excluding
11 exemplars which do not fall within that range.

12 The bullseye test uses the angle defined by the new data vector and the reference
13 vector to locate all exemplars in the current set that match the new spectral vector to the
14 specified angular precision (θ_e) where $\theta_e = \cos^{-1}\epsilon$. Those exemplars are then used by the
15 standard prescreener comparison inequality ($d_i \cdot S_j > 1 - \epsilon$) to make a determination as to
16 whether d_i is similar to S_j .

17 Figure 17 illustrates reference vector R 600 and cone 610 defining a range in which a
18 possible match (rejecting exemplar) may occur. Only exemplars within match zone, 620- 622
19 will be compared to the new data vector. These exemplars, contained in match zone 650, which
20 form an annulus having a center at q_i 660 with maximum thickness $2*\epsilon$, are representative of
21 those vectors which have similar projections onto the reference vector within the selected
22 precision. If an exemplars projection does not fall into the match zone, there is no need to
23 compare that exemplar the to data vector d_i because there the data vector d_i cannot be similar
24 within the desired precision, defined by the thickness of match zone 650.

25 In the bullseye test CHOMPS determines which vectors lie within the annulus by
26 keeping an indexed list of entries in the exemplar table, ordered by angle to the reference

1 vectors. Once the zone is computed, a zig-zag search is performed where the candidate vector
2 is compared to the exemplars with angles starting at θ_0 and deviating in both directions. If the
3 entire zone does not produce a match the vector is determined to contain new information,
4 designated as a new exemplar and added to exemplar set $\{S\}$.

5 Thus through the use of reference vector R and the bullseye test, the number of
6 comparisons necessary to test the entire exemplar set are reduced from several thousand, to
7 something on the order of 20.

8 In an alternative embodiment of the bullseye test a substantial increase the precision
9 and speed of the search is realized by designating multiple reference vectors, each one having
10 its own associated bullseye. One such embodiment is depicted in figure 18, which shows what
11 may be described as a double bullseye cone. A first cone 610 is defined in relation to reference
12 vector R and the second cone 710 is defined in reference to second reference vector R_2 700.

13 Exemplars that are candidates to match the new data vector are located within the intersection
14 of the match zones for each reference vector 777* and 888. Through the use of multiple
15 bullseyes defined by multiple reference vectors, the "hot zone" or area in which a likely
16 matching exemplars must reside is reduced. Only the vectors which simultaneously occupy
17 both match zones are possible matches and need be compared to the new data vector.

18 Referring to the figure 18, the only vector which meets this test requirement is exemplar 620.

19 Thus, CHOMPS is able to conclude that all exemplars in the data set are not rejectors
20 (dissimilar to data vector d), with the possible exception of exemplar 620. By employing
21 CHOMPS and a variation of the bullseye test, the prescreener is able to *exclude* the majority of
22 the exemplar set from the prescreener's comparison test (every exemplar except exemplar
23 620), and designate the incoming data vector as similar or dissimilar to the exemplar set
24 exemplars after a comparison of the data vector to exemplar 620, a single comparison.

25 Excluding the 2 or 3 comparisons for the pop us stack, the only one dot product
26 operation need be processed before the prescreener can determine whether the new data vector

1 contains new data and should be added to the exemplar set.

2 Alternative embodiments of the zone type test may be employed to minimize the
3 computational load on the prescreener depending on mission requirement and the precision
4 desired. For example an avatar bullseye test may be employed. In the avatar bullseye test,
5 only the exemplars with the highest vector rejection totals are used rather than the complete
6 exemplar set.

7 In yet another version of the bullseye test, the match zone width can be diminished by a
8 significant factor with minimal generation of redundant exemplars but with an increase of
9 algorithm speed. For a candidate exemplar which makes an angle θ_0 with the reference vector
10 the width of the match zone is given by δ where:

$$\delta = 2 \sin \theta_0 \sqrt{1 - \epsilon^2}$$

11 The data set describing a scene may be processed using either of three modes which
12 include the Automatic scene segmentation mode, the Full scene mode or the
13 Adaptive/continuous mode.

14 In the Automatic scene segmentation mode, the scene is divided into a series of
15 segments and is processed by the prescreener one segment at a time. Segment size is
16 determined as a function of the exemplar set size. This variation offers several advantages,
17 particularly when attempting to resolve dynamic scenes. With a dynamic or complex scene, in
18 general, a larger exemplar set is required to maintain a specified precision. As the number of
19 exemplars increases, the processing time increases very steeply and the compression ratio
20 decreases.

21 Automatic segmentation may also increase compression efficiency because the dimensionality
22 and the exemplars added into a scene segment in a complex setting, only affect the segment
23 that produced them, and not the possibly simpler segments that follow.

1 The full scene mode is identical to the Automatic segmentation mode, except that a
2 scene is treated as one continuous dataset rather than a number of smaller segments.
3 While operating in the single or multiple segmentation modes, the prescreener feeds the
4 exemplar set to the Adaptive Learning Module (ALM) for endmember computation at the end
5 of each segment or block of data.

6 In the Adaptive mode the same efficiency is accomplished by injecting a finite but
7 renewable lifetime to the exemplars, that is, they are pushed to long term system memory, if
8 they have not produced a spectral match with new vectors for predefined time/frame intervals.
9 The lifetime of the individual exemplars depends on their relationship to the endmembers and
10 the priority assigned to the importance of their spectral patterns. For example, exemplars that
11 contain important subpixel objects are assigned longer lifetimes than ones containing
12 variations of background substances.

13 In the adaptive/continuous mode an ALM cycle is triggered when new exemplars
14 change the dimensionality of the enclosing subspace or when a new exemplar is defined that
15 lies outside the subspace defined by the current endmember set or other criteria, which are
16 mission dependent.

17 When a new exemplar is found, it can be projected into the orthogonal basis set
18 produced by the ALM, to confirm whether the new spectrum produced a subspace
19 dimensionality change. A projection in the endmember space, utilizing the current matched
20 filter vectors, indicates whether the subspace has expanded past the bounds of the current
21 simplex, determined by the shrinkwrap component of the ALM. Either test will signal a
22 trigger to the ALM. Additional criteria, such as the number of image frames since the last
23 ALM, are used to avoid triggering excessive numbers of learning cycles.

24 Referring again to figure 2, the exemplar set data, as computed by prescreener 50 is
25 input 58 into adaptive learning module 30. Learning module 30, computes from the exemplar
26 set, a set of endmembers {E} which together span the current scene. Endmembers are a set of

1 fundamental patterns (vectors) from which any pattern vector in the data set can be
2 reconstructed as a convex combination in reduced dimensional space, to within an error
3 determined by the noise or other error criteria. The requirement that all of the observed
4 spectral vectors d_k be representable as convex combinations of conventional basis vectors,
5 insures that the decomposition makes sense as a physical mixture of constituents, since any
6 such mixture must have this property. The resulting patterns conform as closely as possible to
7 signatures of actual constituents of the scene.

8 Referring now to figure 12, learning module 30, may employ an ordered Gram-Schmidt
9 analysis using salients to construct a reduced dimensional spanning space 125, while retaining
10 the spectral information contained in the exemplar set. The spanning space is constructed
11 based on a spectral uniqueness hierarchy. The observed spectra of the exemplar set, expressed
12 as vector data are then projected into the spanning space 126. A pixel purity determination
13 algorithm may also be employed to define a subset of the salients, followed by a Gram-Schmidt
14 analysis to complete the set. Computation of the endmembers is performed by learning
15 module 30 by projecting the exemplar set data into a reduced dimensional spanning space
16 using a Gram-Schmidt/Salient analysis of the exemplar set data, and employing shrink wrap
17 minimization 127, to minimize the spanning space volume defined using Gram-
18 Schmidt/Salient analysis. The endmembers are defined by the vertices of the hyper triangle
19 defined by the minimized spanning space 128, as illustrated in figure 8.

20 Gram-Schmidt/ Salient Analysis

21 The spanning space is defined by using a Gram-Schmidt / Salient analysis of the
22 exemplar set vectors. In the parameter vector space which contains the exemplar set data, one
23 first determines the two vectors which are furthest apart in the space, then, in the plane formed
24 by these two vectors, select two mutually orthogonal vectors which lie in the plane. These
25 mutually orthogonal vectors are for convenience called basis vectors, for reasons made
26 apparent below. Next, select the vector in the data cube which is furthest from the plane and
27

1 identify the hyperplane in which the basis vectors, and the newly selected vector, lie, and select
2 a third basis vector such that it lies in the hyperplane and is mutually orthogonal to the other
3 two basis vectors. This process is repeated, and one accumulates more and more mutually
4 orthogonal basis vectors, until the most distant remaining vector is found to be within a
5 preselected distance of the hyperplane containing all the basis vectors. At this point, the
6 exemplar set vectors are projected onto the reduced dimensional space defined by these basis
7 vectors.

8 Through the reduction of the dimension of the vector space in which one must work,
9 CHOMPS correspondingly reduces the number of operations one must do to perform any
10 calculation. Since none of the data vectors lie very far outside the hypervolume spanned by the
11 basis vectors, projecting the vectors into this subspace will change their magnitude or
12 direction very little, i.e. projection merely sheds components of each vector which were small
13 already. Furthermore, because such components are necessarily too small to correspond to
14 significant image features, these components are disproportionately likely to be noise, and
15 discarding them will increase the system's signal to noise ratio.

16
17
18 Gram-Schmidt \ Salient analysis of the exemplar set data is performed in accordance
19 with the following algorithm:
20

21
22 a) Designate the two exemplar vectors farthest apart, V_1 and V_2 . Figure 4 illustrates
23 the orientation of V_1 and V_2 and the plane that V_1 and V_2 define.

24
25 b) Generate a 2 dimensional orthogonal set of basis vectors from V_1 and V_2 labeled V_{10}
26 and V_{20} in the plane defined by V_1 and V_2 , labeled as PV_{012} as illustrated in Figure 5.

27
28 c) Determine the salient vector (vector displaced farthest from plane) in relation to
29 plane PV_{012} , defined in Figure 6 as $\sim S_1$.

30
31 d) The salient $\sim S_1$ can be represented as a sum of vectors $S_{1\perp}$ and $S_{1\parallel}$, where $S_{1\perp}$ is
32 orthogonal to the plane PV_{012} and $S_{1\parallel}$ lies in the plane. Use the Gram-Schmidt procedure to
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1 find $S_{1\perp}$, and call this V_{30} . V_{10} , V_{20} and V_{30} now define a subspace in 3 dimensions. See the
2
3 figure 7. representation of the subspace created by this step.

4
5 e) Select the salient $\sim S_2$ which is the exemplar vector farthest from the subspace
6
7 defined by step (d).

8
9 f) Generate a new orthogonal direction from $\sim S_2$ defined as V_{40} . V_{40} coupled with V_{10} ,
10
11 V_{20} , and V_{30} now defines a subspace of 4 dimensions.

12
13 g) Steps (e) and (f) are repeated to define a spanning space of N dimensions. The
14
15 distance out of the current subspace of the salient selected at each step is the maximum
16
17 residual error which would be incurred by projecting all of the exemplars into the subspace.
18
19 This decreases at each stage, until the remaining error is within a specified error tolerance. At
20
21 this point the subspace construction process is complete. The value of N is the number of
22
23 dimensions necessary to allow the projection of the exemplar set data vectors into the subspace
24
25 while at the same time preserving important but infrequent signatures.

26
27 h) Project all of the exemplar set data into the spanning space defined in steps (a)-(g).
28
29 The Gram-Schmidt \ Salient analysis is the preferred subspace determination for CHOMPs,
30
31 however CHOMPs is not limited to the Gram-Schmidt \ Salient method for subspace
32
33 determination. Other methods known in the art may be employed including but not limited to
34
35 PCA methods, and Pixel Purity methods.

36 Shrink Wrap

37
38 Once the N -dimensional spanning space is defined, a convex manifold in the form of a
39

hypertriangle within the spanning space is generated using shrink wrap minimization. Shrink wrap minimization of the spanning space is a simple minimization operation, in which the volume of the manifold is reduced, while maintaining the condition that all of the data vectors projected into the reduced dimensional space are contained within the hypertriangle. The vertices of the hypertriangle are the endmembers, and the volume defined by the hypertriangle itself is the locus of all possible mixtures (convex combinations) of endmembers. The shrink wrap process determines good approximations of the physical constituents of the scene (endmembers), by insuring that the shape and orientation of the hypertriangle conforms as closely as possible to the actual distribution of the data vectors (exemplars). The exemplars are assumed to be mixtures of the actual constituents. The number of endmembers is equal to the dimension of the spanning space.

The salients are used to guide the shrink wrap process. Referring to figure 8, hypertriangle $T_{S_1S_2S_3}$ is defined by salient vectors, however, other vectors which include data may not be within the spanning space which $T_{S_1S_2S_3}$ defines, as depicted in figure 9. The shrink wrap operation must satisfy the condition that all of the data vectors projected into the spanning space be contained within the volume defined by convex manifold $T_{E_1E_2E_3}$. The shrink wrap operation starts with $T_{E_1E_2E_3} = T_{S_1S_2S_3}$ and then expands or contracts the triangle $T_{E_1E_2E_3}$ by manipulating the vertices, E_1 , E_2 and E_3 or by manipulating the orientation of planes that define $T_{E_1E_2E_3}$, by the minimal amount to fulfill the above stated condition.

For purposes of example, the method described above and the following methods have been found effective, however, a combination of one or more of the disclosed methods, or any other minimization method which maintains the condition that the majority of the data vectors be contained within the minimized space is suitable.

Adaptive learning module 30 generates a set of filter vectors $\{F_i\}$ and endmembers $\{E_i\}$,

1 $E_2, E_3, \dots, E_N\}$ in accordance with one of the following procedures, or variants thereof:

2 Method 1

3 With reference to figure 10a, find a set of endmembers $\{E_i\}$ such that each endmember E_i is
 4 matched to a salient vector $\sim S_i$, and is as close as possible to its salient, subject to the condition
 5 that all the data vectors are inside the hypertriangle with vertices $\{E_i\}$. I.e., minimize

$$C = \sum_{i=1}^{N_d} (E_i - S_i)^2$$

6 subject to the constraints $F_i \circ d_k \geq 0$ for all i and k . The filter vectors are computed from the
 7 candidate endmembers as described above. This constraint condition means that all the
 8 coefficients of the decomposition of d_k into endmembers are non-negative, which is equivalent
 9 to saying that all d_k are inside $T_{E_1 E_2 \dots E_N}$. This is a nonlinear constrained optimization problem
 10 which can be solved approximately and quickly using various iterative constrained gradient
 11 methods.

12 Method 2

13 Compute a set of filter vectors $\{F_{si}\}$ from the salients $\{\sim S_i\}$, using the formulas previously
 14 provided. These vectors will not, in general satisfy the shrink wrapping constraints see figure
 15 10b. Find a new set of Filter vectors $\{F_i\}$ such that each Filter vector F_i is matched to a
 16 salient Filter vector F_{si} , and is as close as possible to its salient filter, subject to the condition
 17 that all the data vectors are inside the hypertriangle. I.e., minimize

18
$$C = (F_i - F_{si})^2$$

19 subject to the constraints $F_i \circ d_k \geq 0$ for all k . This is a set of independent quadratic
 20 programming problems with linear constraints, which can be solved in parallel using standard
 21 methods. The decoupling of the individual filter vector calculations increases computational

1 to manipulating the plane faces of the triangle instead of the vertices. Given solutions for the
 2 Filter vectors, find the endmembers using the same procedure used to compute Filter vectors
 3 from endmembers (the defining relationships are symmetric except for a normalization
 4 constant).

5 Method 3

6 With reference to figure 11, find an approximate centroid C_d of the set of exemplar vectors,
 7 and then find the hyperplane of dimension one less than the dimension of the enclosing space
 8 which is closest to the centroid. Hyperplane 120 divides the complete subspace into two
 9 halves, and the minimization is subject to the constraint that all the exemplar vectors d_k must
 10 be in the same half-space as the centroid $\{c_d\}$. The normal to the optimal hyperplane 120, is
 11 F_1 , the first filter vector. and the condition that all the exemplars are in the same half-space is
 12 equivalent to the constraint that $F_1 \cdot d_k \geq 0$ for all k . This process is equivalent to finding a
 13 vector F_1 with a fixed magnitude which minimizes the dot product $F_1 \cdot C_d$ subject to the
 14 constraint $F_1 \cdot d_k \geq 0$ for all k . As such it is amenable to solution using conventional
 15 constrained optimization methods. The hypertriangle $T_{E_1 E_2 E_3}$ can be constructed out of a set of
 16 suitably chosen optimal (locally minimal distance to the centroid) bounding hyperplanes which
 17 form the faces of the convex manifold. The normal to each face defines the associated filter
 18 vector. Again, the endmembers can be determined from the Filter vectors at the end of the
 19 shrink wrapping process.

20 Referring to figure 12 and figure 2, once the endmembers and filter vectors are
 21 computed adaptive learning module 30 stores this endmember and filter vector data, along
 22 with data reflecting the exemplar set, and source vectors 33 for future recall. The adaptive
 23 learning module 30 then searches the exemplar set for any changes 148. If the system detects
 24 change in the exemplar set 99, the basis and shrink wrap processes are repeated 141. This

1 change in the exemplar set 99, the basis and shrink wrap processes are repeated 141. This
 2 process allows the system to continually learn and adapt to changes in the environment.
 3 Endmember data and the accompanying exemplar set and source data can be labeled as being
 4 consistent with a particular threat or target allowing the system to learn and remember the
 5 signature of specific targets in real time 34.

6 Again, referring to figure 2, the filter vectors and endmember data stream are
 7 transmitted from learning module 30, to demixer module 40, for computation of the
 8 endmember coefficients. The original data set from the sensor is also transmitted to demixer
 9 module 20 through the first processor pipe.

10 Demixer module 20 may contain several processors, each of which convolves the
 11 unprocessed data vector with a different filter vector. These operations could be performed
 12 sequentially on a single fast processor, but in the best mode they are performed in parallel.
 13 The output of demixer module 20, is a vector called the endmember coefficient vector, the jth
 14 element of which indicates the fraction of the jth fundamental pattern which is present in the
 15 unprocessed data vector. The endmember coefficients indicate the amplitude of the signal from
 16 the associated endmember, in a mixed spectrum.

17 Demixer module 20 convolves the unprocessed data vector and computes the
 18 endmember coefficient in accordance with the equation;

$$F_j \cdot d_k = \sum_{j=1}^n c_{jk} F_j \cdot E_j + F_j \cdot N_k \approx c_{jk}$$

19 where F_j = said filter vector, d_k = said data set, c_{jk} = said endmember coefficient, N_k = noise
 20 vector and E_j = said endmember.

21 Demixer module 20 next computes the fraction coefficient 131, which tells what

1 percentage of the photons from the given pixel are associated with the endmember in
 2 accordance to the equation:

$$c_{jk \text{ fraction}} = \frac{c_j A(E)_j}{A(d_k)}$$

3 where $A(d_k)$ is the area under vector d_k , i.e. the sum of the elements of d_k .

4 Figure 13 illustrates the flowchart for demixer module operation including the demixer
 5 module's 20 function in the system's learning process. If the pixel information passed from the
 6 preprocessor indicates bad data or an unlearned spectrum 133, 134 demixer module 20 routes
 7 that information to the display/ output module 40 with a notation of the status of the pixel
 8 data 135, 136.

9 The spectral information, filter vectors, and endmember coefficients is passed to the
 10 display/ output module 40 for display and further processing 138. The spectral characteristics
 11 of the data is stored, transmitted or displayed in terms of endmembers and endmember
 12 coefficients maintaining the relation:

13

$$d_k = \sum_{j=1}^n c_{kj} E_j + N_k$$

14 where d_k = said data set, c_{kj} = said endmember coefficient and c is ≥ 0 , N_k = noise and E_j =
 15 said endmember.

16 CHOMPS feature three compression modes which provide significant compression of
 17 the massive data stream coming from the sensor. These compression modes in a preferred
 18 embodiment take advantage of the priority and zone searching techniques disclosed above.

1 employs the basic IHPS algorithm, using the computational management techniques described
2 in this text, and produces a compressed data set which expresses the scene as, a set of fraction
3 planes belonging to each endmember E . Compression results from the low dimensional space
4 in comparison to the number of bands employed by the sensor.

5 For purposes of example, assume a sensor operates in 200 bands, the data set produced
6 by that sensor as input for IHPS will thus tend to have what approaches 200,000,000 scalar
7 values. This assumes only 1,000,000 pixels in a scene. IHPS expresses the scene as fraction
8 planes. The IHPS endmember form compresses the data stream by the ratio:

$$\frac{N_B}{N_E}$$

9 where N_B is the number of bands and N_E is the number of endmembers necessary to describe
10 the scene.

11 For many natural scenes at a reasonably small loss rate, IHPS requires on the order of
12 10 endmembers to describe the scene which results in a compression ratio of 20:1 for a 200
13 band sensor.

14 Following each ALM cycle, all exemplars for the segment are either left uncompressed,
15 are projected into the orthogonal basis space or are projected to the current shrinkwrap.

16 Referring to figure 19 which shows a simple logical flowchart of the second or
17 wavespace compression packaging mode in which the data is expressed in terms of the
18 exemplars and two maps used for reconstruction of the data set d . The complete data set is
19 received from the sensor 701, containing for purposes of example approximately 200 million
20 scalar values describing a scene. CHOMPS next uses the prescreener to perform the
21 prescreener comparison 702, and reduces the complete data set to an exemplar set 703. The

1 exemplar set size can be adjusted by the user on the basis or the precision desired or other
2 mission requirements, but for purposes of example may be 10,000 vectors in size (2,000,000
3 scalars). CHOMPS uses information from the prescreener comparisons to compile a rejector
4 index or rejector plane 704. The rejector plane simply records which exemplar rejected each
5 new data vector received by the prescreener. CHOMPS also builds an intensity map 705,
6 which records the intensity of each new data vector input into the prescreener. The intensity
7 map and rejector index is downloaded along with the complete exemplar set, expressed in
8 wavespace 706.

9 Thus the data stream of 200 million scalars is expressed as approximately 10,000
10 exemplars each having 200 elements and the map information, each map containing 1 scalar
11 for each of the 1 million data set vector, rather than the 200 scalar values for each data vector.
12 This represents a data set compression of the approaching 50:1 using the wavespace mode.

13 The third compression packaging mode is similar to the wavespace compression mode
14 except that CHOMPS projects the exemplars into endmember space for additional
15 compression.

16 Referring to figure 20 which is a flowchart of the endmember compression mode, the data set
17 is received in the prescreener from the sensor 555 and compared to the existing exemplars 556,
18 just as in the wavespace compression mode 700. The prescreener builds the exemplar set 557,
19 rejector index 558, and an intensity map 559 identical to that in the wavespace compression
20 mode 700. However, in the endmember compression mode CHOMPS sends the exemplar set
21 to the ALM 560, for computation of endmembers 561. The exemplar set is thus projected into
22 endmember space 562, realizing additional compression. The compressed exemplar set is
23 expressed in endmember space, each exemplar now expressed as 10 or so scalars rather than
24 the 200 or so scalar values necessary in wavespace, assuming a sensor having 200 bands. The

1 endmembers expressed in wavespace are added to facilitate reconstruction of the scene. The
2 rejector index and intensity map are also output for reconstruction of the data set.
3 Endmember compression realizes a 100:1 reduction in the data transfer necessary to describe a
4 scene. The output packet of the compressed segment data consists of the exemplar list in any
5 of the projections above, the endmembers or basis vectors and the two decoding maps.
6 Additional information can be injected, such as the number of vectors replaced by each
7 exemplar.

8 CHOMPS thus uses the Adaptive Learning Module Pipeline to construct a compressed
9 data set, along with the necessary scene mapping data, facilitating the efficient storage,
10 download and the later reconstruction of the complete data set with minimal deterioration of
11 signal information.

12 In a preferred embodiment the CHOMPS employs the following algorithm:

- 13 a) Receive data vector d_i into the prescreener.
- 14 b) Designate priority exemplars from the existing exemplar set and perform priority
15 testing according to the relation $(d \circ S = 1 > \epsilon)$ of the data vector d_i using the exemplars S_j
16 designated with the higher priority.
- 17 c) If priority testing generates a match condition go to (a), if no match condition produced
18 after N iterations, continue.
- 19 d) Select at least one reference point or reference vector.
- 20 e) Designate at least one match zone and perform zone testing on data vector d_i according
21 to the relation $(d \circ S = 1 > \epsilon)$ using only those exemplars S_j which are contained (to the desired
22 precision) within the match zone.
- 23 f) If zone testing generates a match condition go the step (a), if no match condition is
24 produced add d_i to the exemplar set and go get next data vector d_{i+1} , exemplars are exhausted.
25 g) Perform compression packaging via full IHPS mode, wavespace mode, exemplar mode
26 or a combination thereof.

27 Obviously, many modifications and variations of the present invention are possible in
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1 light of the above teachings. For example this invention may be practiced without the use of a
2 parallel processing architecture, different combinations of zone and priority testing may be
3 employed, ie., zone testing may be employed without priority testing or standard compression
4 algorithms may be employed to compress the intensity map and rejectors index.

5 It is therefore understood that, within the scope of the appended claims, the invention
6 may be practiced otherwise than as specifically described.

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2 We Claim:

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4 1. A system comprising:

5 sensor means for generating a plurality of data vectors;

6 means for producing endmember vectors responsive to said generating;

7 wherein said means for producing comprises a module adapted to reduce the spanning
8 space of said data vectors by application of the Graham-Schmidt algorithm using salients.

9

10 2. A sensor system comprising:

11 means for collecting data,

12 an exemplar set, said exemplar set comprising exemplar set members;

13 means for generating a compressed data set, said data set comprising data set members

14 wherein;

15 said means for generating compares said data set members with respective ones of said

16 exemplar set members effective to characterize said data set members as similar or dissimilar

17 to said exemplar set members according to a preselected criterion, and

18 means for including said data set members characterized as similar in said exemplar

19 set;

20 means for generating the endmember vectors of said exemplar set;

21 means for demixing said data set.

22

23 3. A system comprising:

24 sensor means for generating a plurality of data vectors;

1 means for producing endmember vectors responsive to said means for generating;
2 wherein said means for producing comprises a module adapted to reduce the spanning
3 space of said data vectors by application of the Graham-Schmidt algorithm using salients;
4 means for compression said plurality of data vectors by employing the CHOMPs
5 algorithm.

6 4. A method for processing hyperspectral data comprising:
7 generating a plurality of data vectors;
8 producing endmember vectors responsive to said generating;
9 wherein said producing comprises reducing the spanning space of said data vectors by
10 application of the Graham-Schmidt algorithm using salients;
11 compressing said plurality of data vectors by application of the CHOMPs algorithm.
12

13 5. A method for processing multi dimensional data comprising:
14 collecting data,
15 generating a exemplar set, said exemplar set comprising exemplar set members;
16 generating a compressed data set, said data set comprising data set members wherein;
17 comparing said data set members with respective ones of said exemplar set members
18 effective to characterize said data set members as similar or dissimilar to said exemplar set
19 members according to a preselected criterion, and
20 including said data set members characterized as similar in said exemplar set.
21 generating the endmember vectors of said exemplar set;
22 demixing said data set.
23

24 6. A method for compressing a data stream comprising:

1 collecting data,
2 generating a exemplar set, said exemplar set comprising exemplar set members;
3 generating a compressed data set, said data set comprising data set members wherein;
4 said generating compares said data set members with respective ones of said exemplar
5 set members effective to characterize said data set members as similar or dissimilar to said
6 exemplar set members according to a preselected criterion, and
7 including said data set members characterized as similar in said exemplar set.
8 generating the endmember vectors of said exemplar set.
9
10

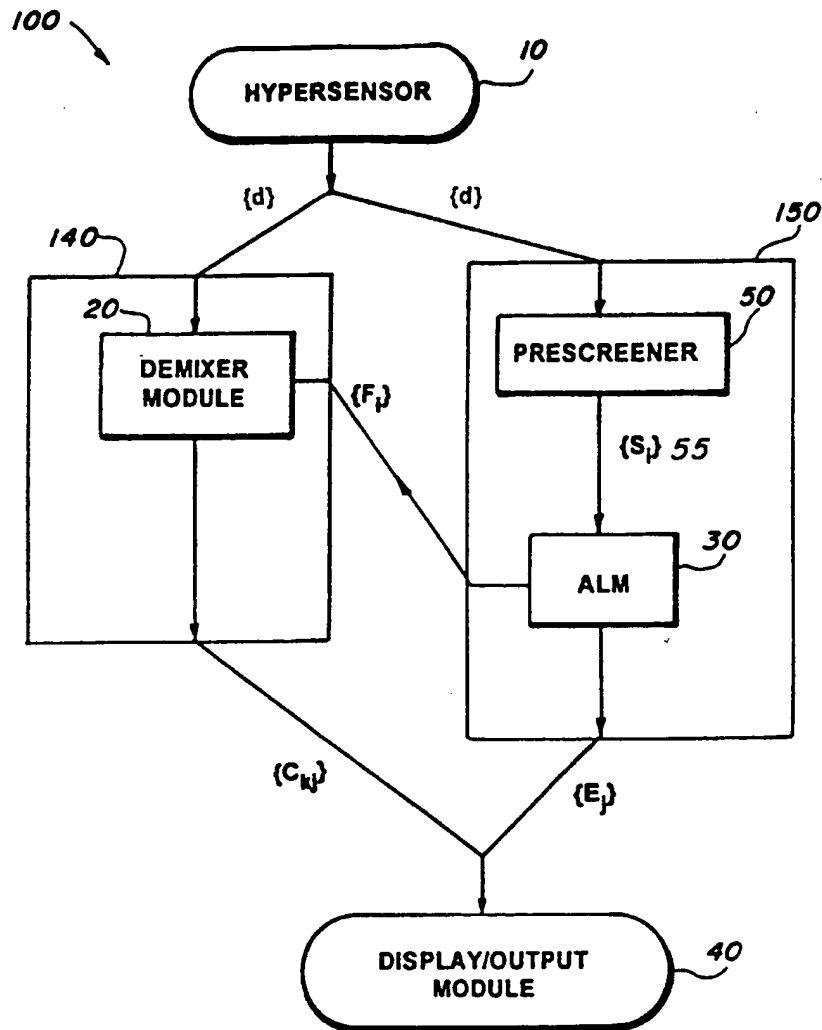


FIG. 2

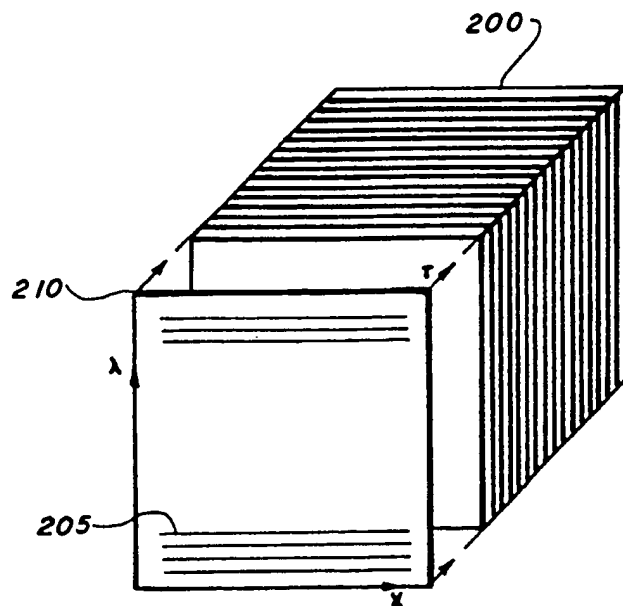


FIG. 1

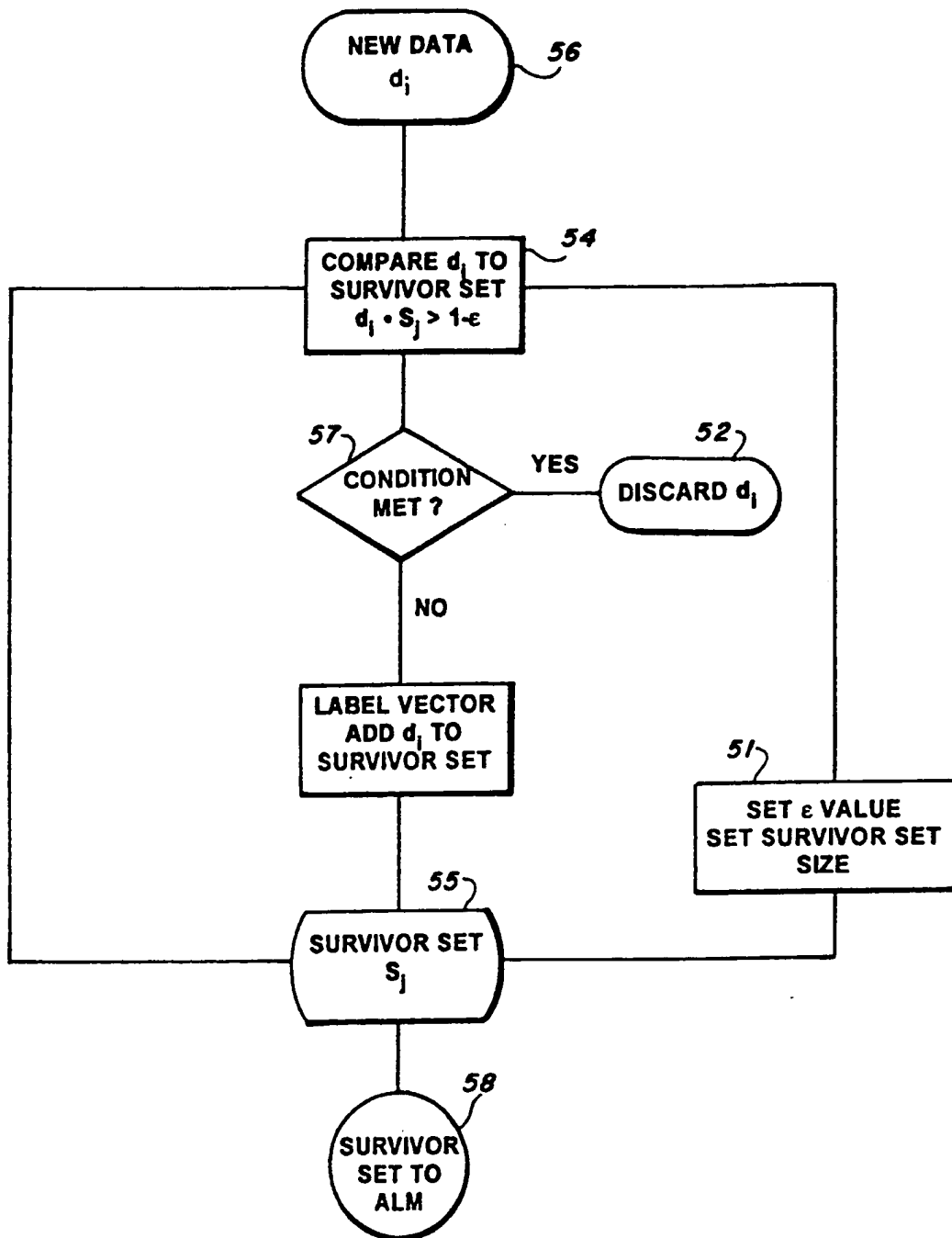


FIG. 3

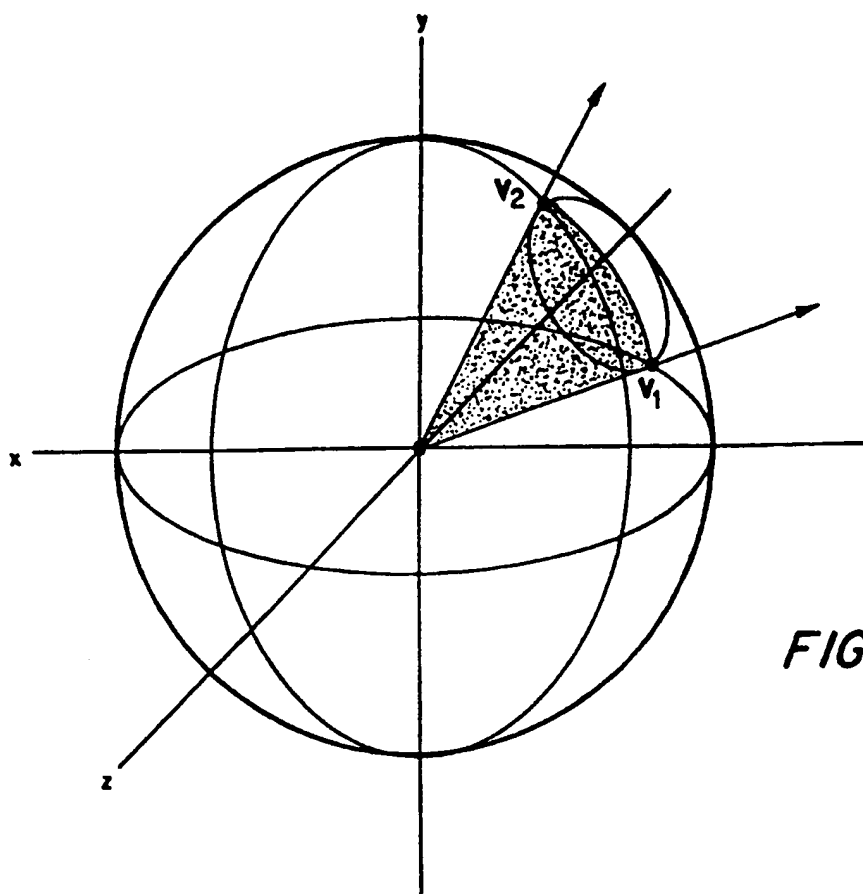


FIG. 4

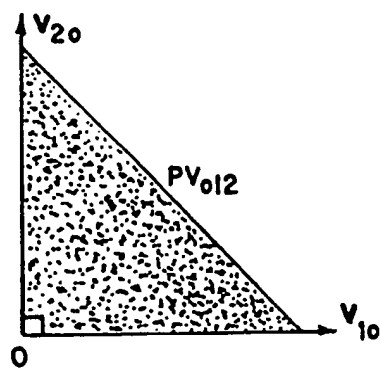


FIG. 5

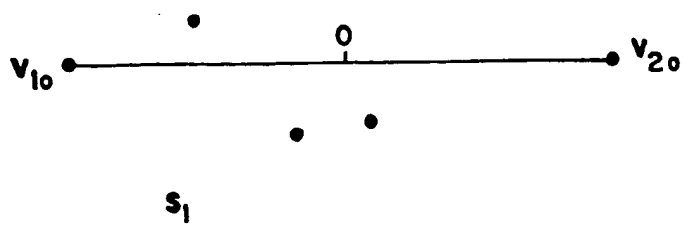


FIG. 6

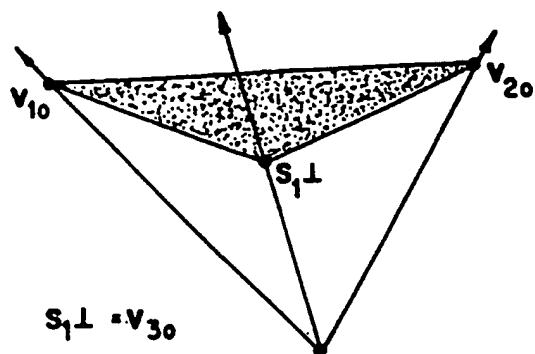


FIG. 7

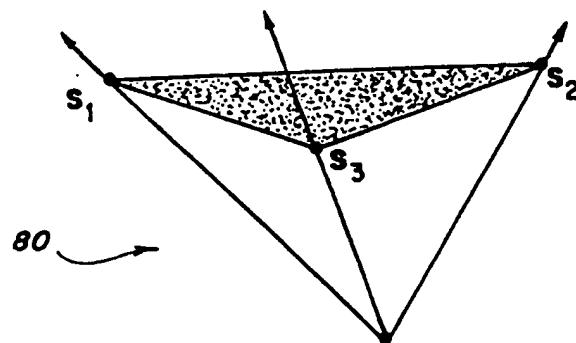


FIG. 8

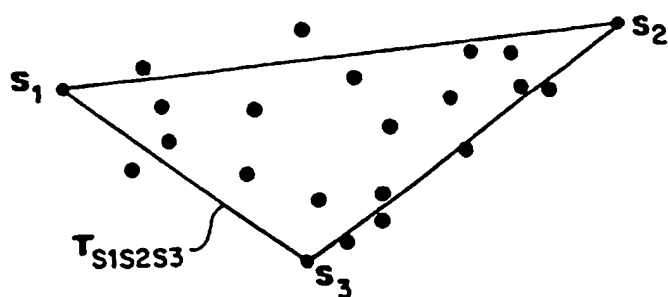
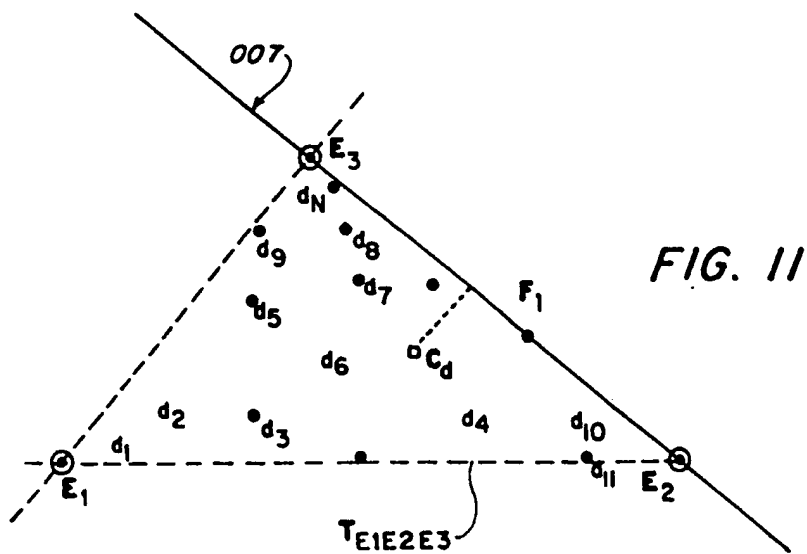
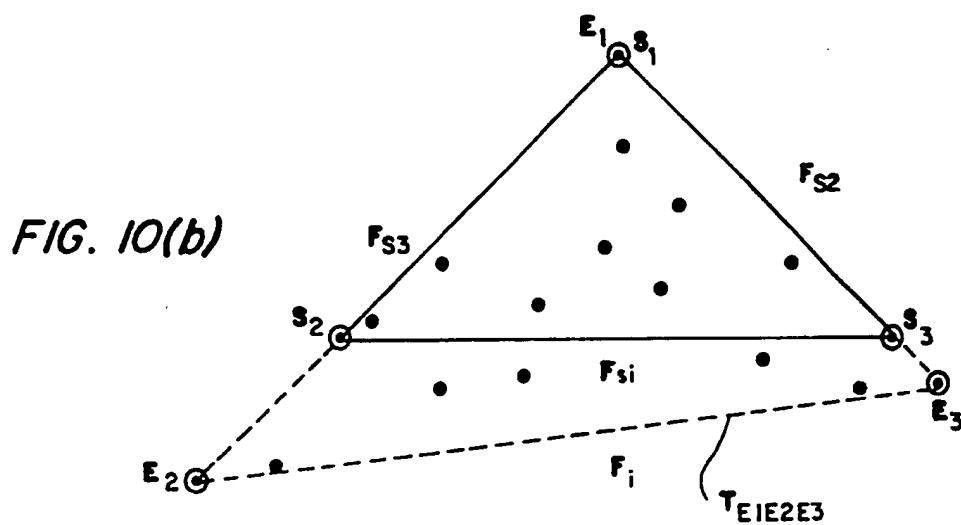
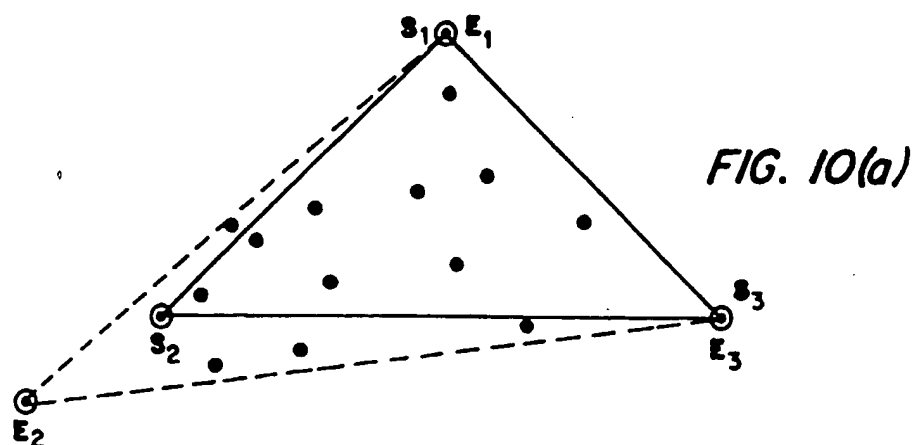
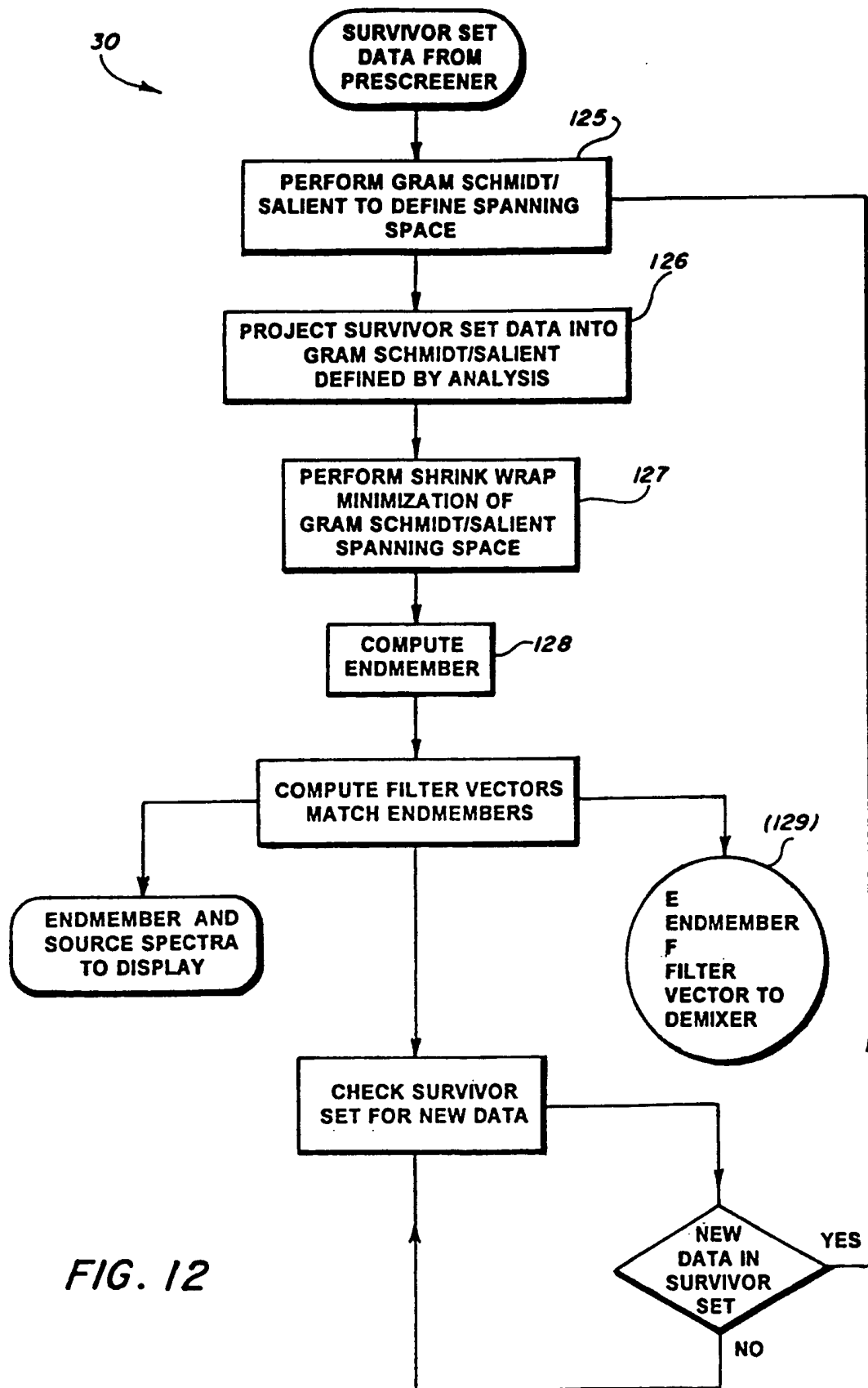
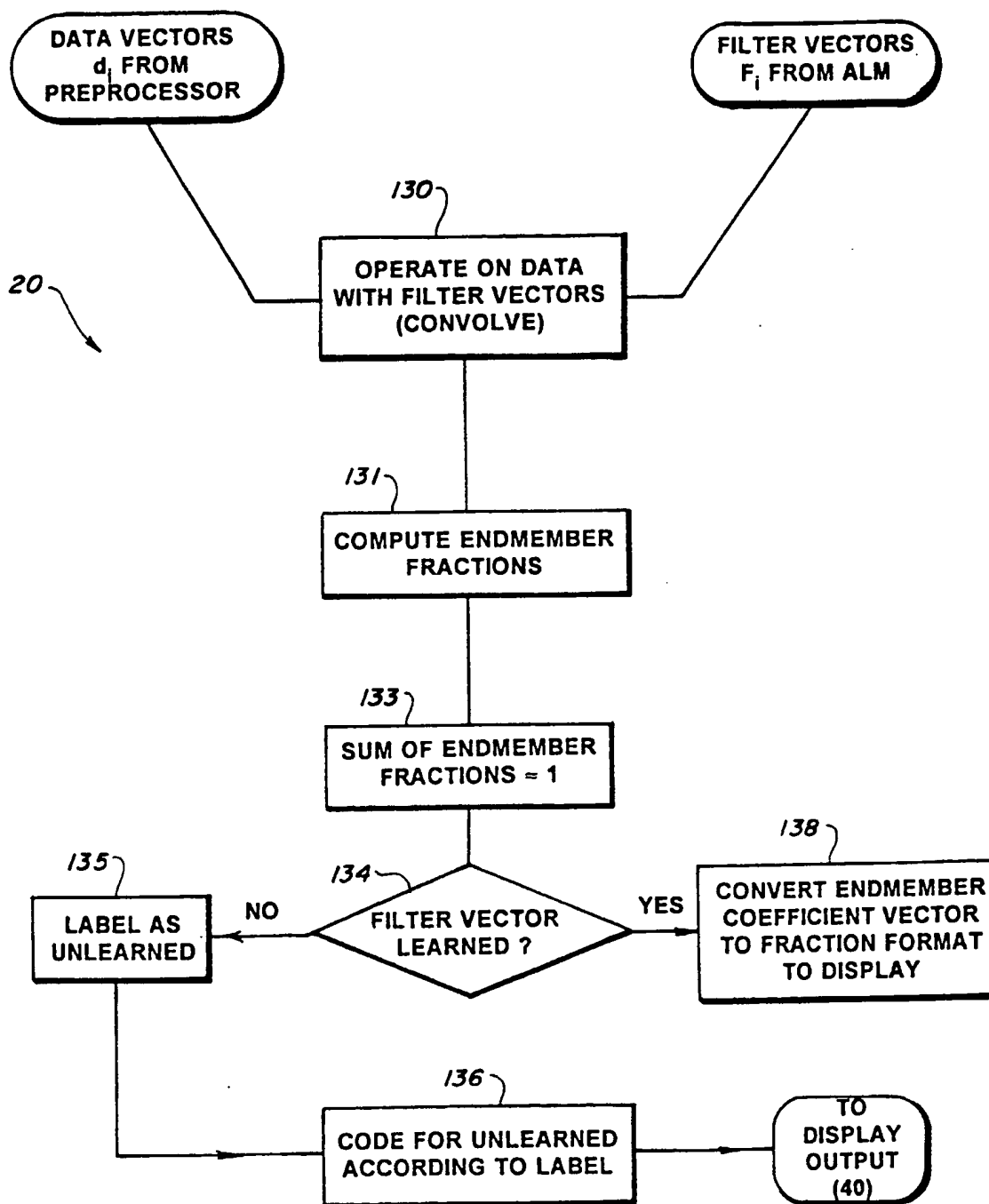


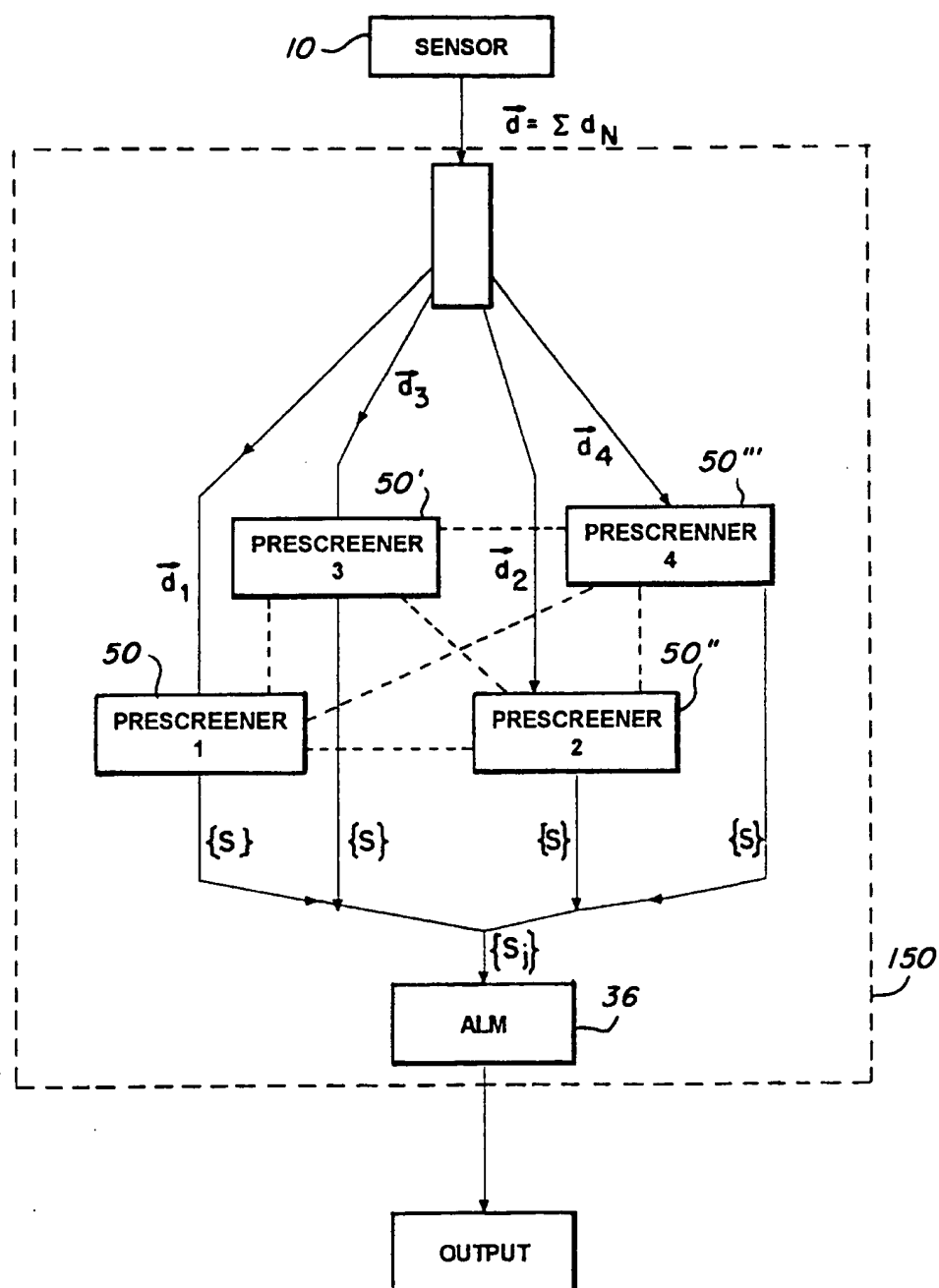
FIG. 9

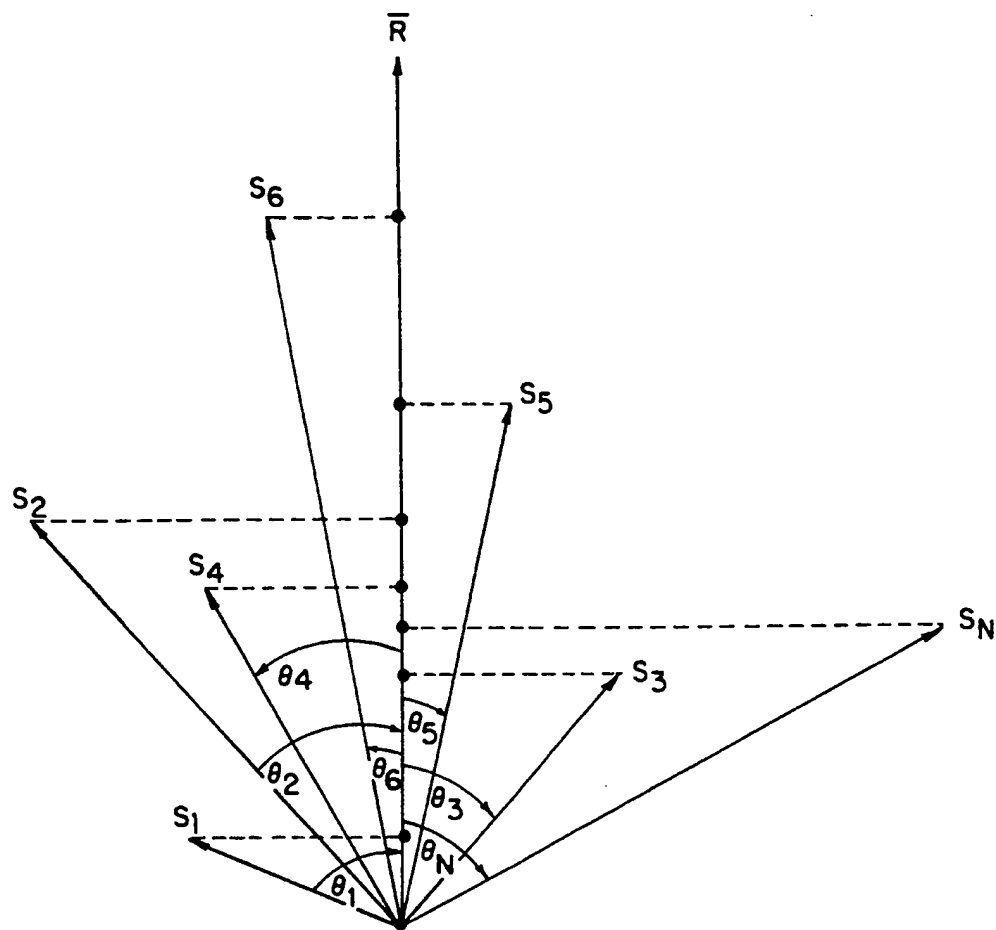
$$T_{S1S2S3} = T_{E1E2E3} @ 1=0$$







**FIG. 14**

**FIG. 15**

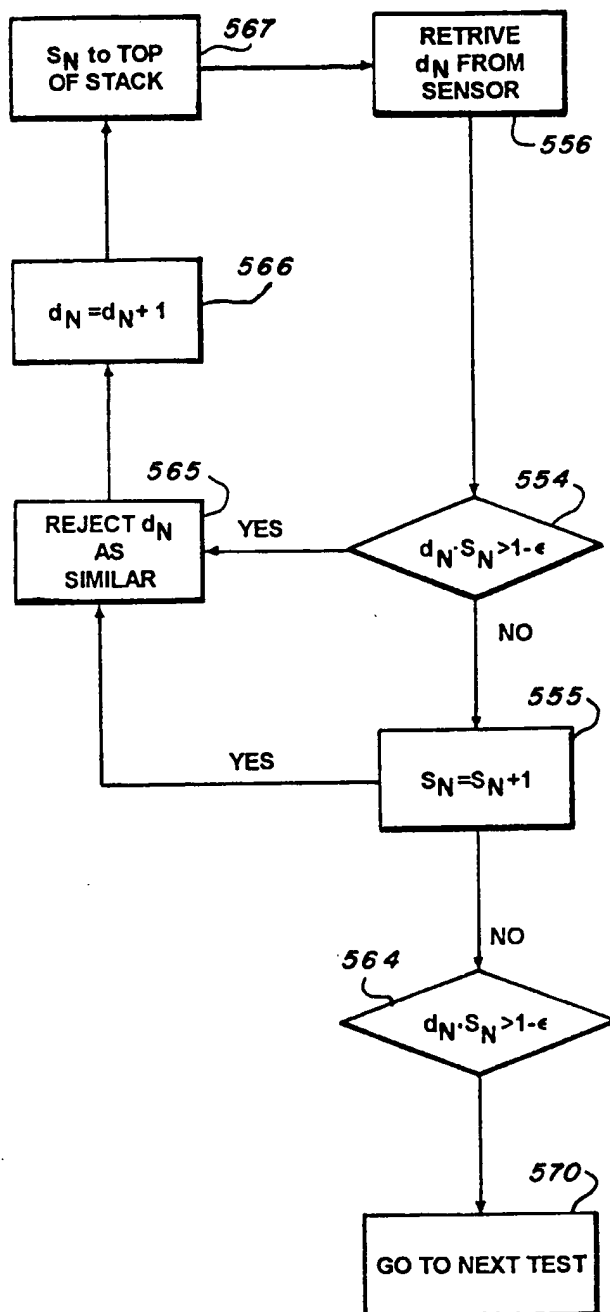


FIG. 16

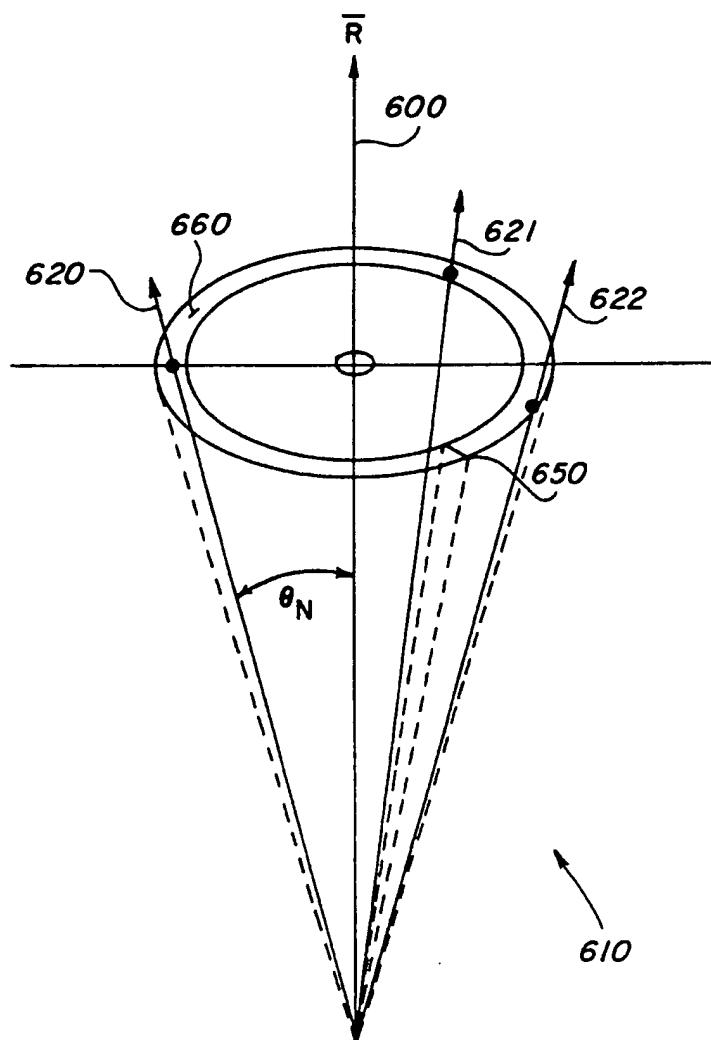


FIG. 17

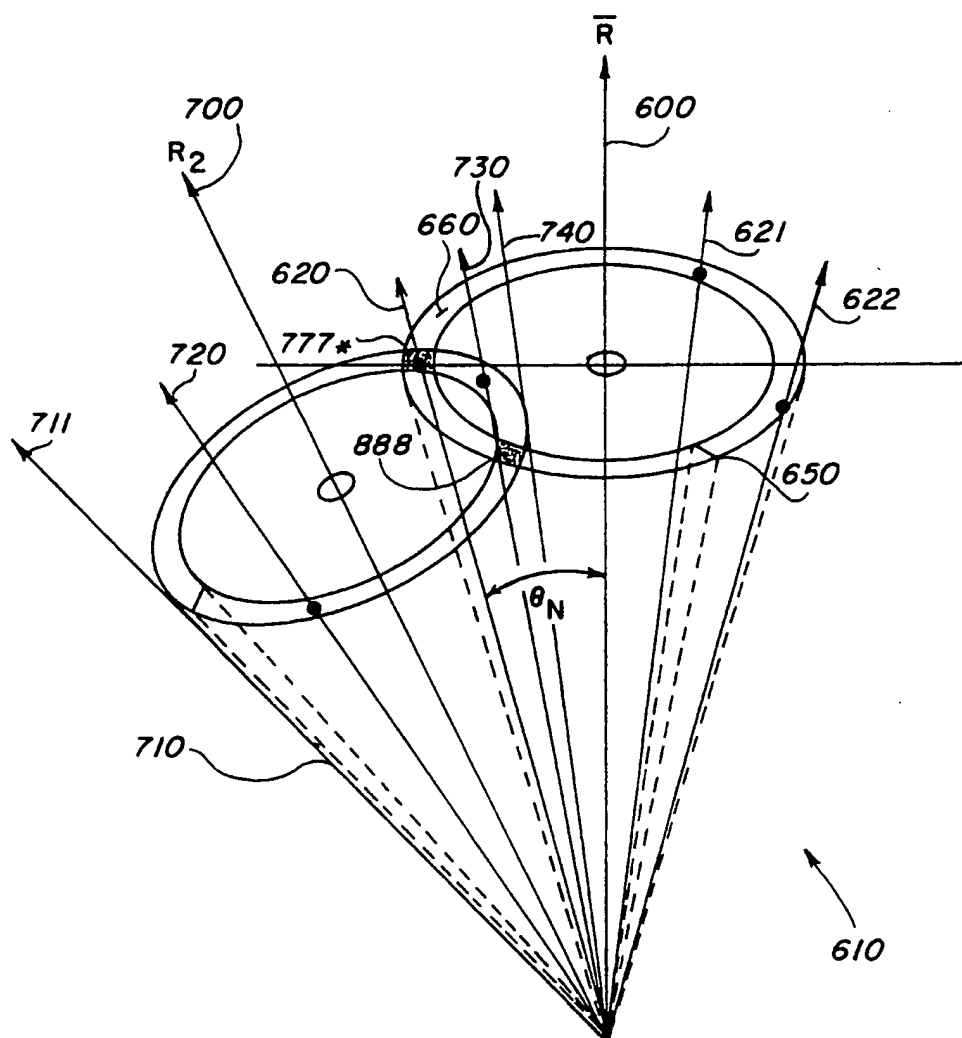


FIG. 18

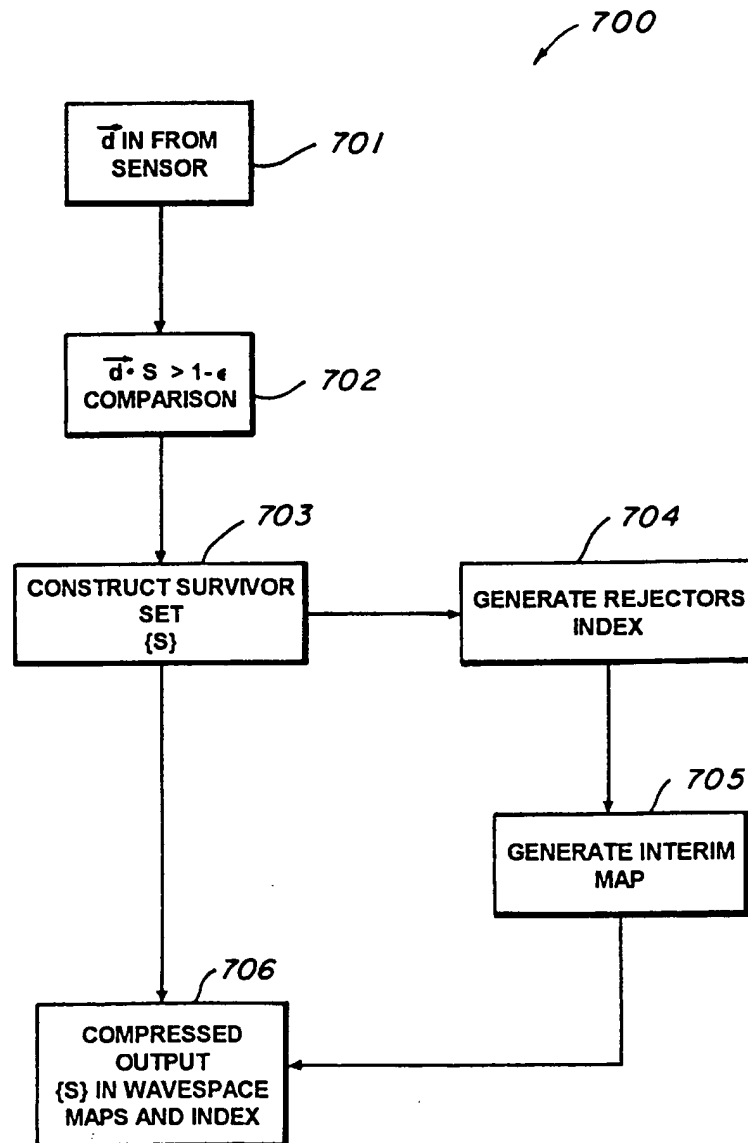


FIG. 19

FIG. 20

